The Detection of Outlying Fire Service's Reports

FCA Driven Analytics

Adam Krasuski[1] and Piotr Wasilewski[2]

[1] Section of Computer Science
The Main School of Fire Service
ul. Słowackiego 52/54, 01-629 Warsaw, Poland
[2] Institute of Informatics, University of Warsaw
ul. Banacha 2, 02-097 Warsaw, Poland
krasuski@inf.sgsp.edu.pl, piotr@mimuw.edu.pl

Abstract. We present a methodology for improving the detection of outlying Fire Service's reports based on domain knowledge and dialogue with Fire & Rescue domain experts. The outlying report is considered as element which is significantly different from the remaining data. Outliers are defined and searched on the basis of domain knowledge and dialogue with experts. We face the problem of reducing high data dimensionality without loosing specificity and real complexity of reported incidents. We solve this problem by introducing a knowledge based generalization level intermediating between analysed data and experts domain knowledge. In the methodology we use the Formal Concept Analysis methods for both generation appropriate categories from data and as tools supporting communication with domain experts. We conducted two experiments in finding two types of outliers in which outliers detection was supported by domain experts.

Keywords: outliers detection, formal concept analysis, fire service

1 Introduction

Each of approximately 500 Fire and Rescue Unit (JRG) of the State Fire Service of Poland (PSP) conducts around 3 fire and rescue actions on daily basis. There is a report created in the internal computer system of PSP named EWID after every single action. The reports comply to the requirements set by regulations [1]. The data collected in EWID database is divided into two sections – structured (database fields) and unstructured (description in natural language (NL)).

Every day ca. 1 500 reports flow into the Headquarter (HQ) of the State Fire Service of Poland. Due to the number of attributes which commanders have to select during the report submission (about 500), many reports have wrong or omitted information. These errors distort future statistics and impede analyses of the data. There is a special department in HQ which is delegated to run data analysis and check the correctness of the reports. Unfortunately, the large number of the reports which are to be checked, forces use of sampling. Therefore, many reports are saved in EWID with factual errors. There is also another type of reports which should be intercepted. These are the reports describing very rare occurrence of objects involved in fire, not typical flow of events during the rescue action, unusual combination of threats at the fire ground or weird method used by commanders. This type of incidents due to their peculiarity may (in the future) result in large number of casualties. They should be analysed, discussed and in extreme cases new procedures should be introduced.

In the EWID database, there is no difference between these two types of the reports in question (misspelled and real outlier). From data representation point of view, they contain rare attribute value or attribute values combination. Therefore, the methods focused on detecting them should be generally similar or the same. Whereas successful detecting of this atypical reports may result in improvement of public safety and more reliable analysis of the data.

The EWID till now has collected approximately 7 million incidents. Undoubtedly, EWID is the rich source of information about threats and appropriate but also incorrect methods of their elimination. However, without doubt this database is difficult to process and analyse. The main reason for this is curse of dimensionality (500 attributes) and the necessity of processing of natural language descriptions. The simple methods like filtering, aggregating or statistical analysis do not reflect the phenomena behind the data. Therefore more sophisticated methods are needed in order to discover the knowledge. Recently few works were published, which present the more advanced approach to analysing such data. They used the methods from data mining domain [8, 19, 12], text mining [14] or even granular computing approach [13]. However, in our opinion most promising algorithms of knowledge discovery should interact with domain experts while working. In the data analysing like Fire Service reports an expert who can interpret the semantics of data, find interesting patterns or cases and can set the direction of the research plays a pivotal rôle. The works of Poelmans et. al (see [3, 16, 15, 17]) show that combination of domain experts with tools which can pre-process the information and present it in the way convenient for the experts, may help discovering important information from the structured and unstructured data (police reports).

The Formal Concept Analysis (FCA) is a theory of data analysis which identifies conceptual structures among data sets [5]. The strength of FCA in data analysis is grouping and structuring the information hidden in dataset and its presentation in a perspective convenient for the domain experts. The selected data are presented to experts and they can recognise the interesting pattern or data structure. In the scope of analysing of the Fire Service reports, FCA structures the data, creating at the same time the concepts limited by the attributes and set of objects which posses the same attribute values. For example it may create the concept of incidents which were extinguished by the same equipment set. However, in order to recognise not trivial concepts the interaction with experts is needed.

In this paper we propose a methodology for improving the detection of outlying reports based on domain knowledge and dialogue with domain experts. We analyse reports from the database of Polish Fire Service's reports, with support of Fire & Rescue domain experts. Presented methods are based on the Formal Concept Analysis (FCA) approach. The rest of this paper is structured as follows. In Section 2 we give the definition of outlying reports which is based on atypical emergencies and F&R methods. In Section 3 we describe the dataset. In Section 4 we present our method of the analysis focused on detecting the atypical emergencies, F&R methods or relation between them. In Section 5 we describe the experiments which we conduct to validate our methodology. The article is concluded with the interpretation of research results and the perspectives for future work.

2 The Outlying Reports

The State Fire Service of Poland responses many types of incidents. Main categories include: fires, road incidents, industry disasters, natural calamities, collapses. For every of these main categories we can outline the several levels of subcategories. This taxonomy complies to the regulations set by [1]. However even in the lowest subcategories of the taxonomy, experts can define, according to domain knowledge, particular subclasses of similar events. There are also incidents which cannot be categorized or attached to a particular subclass even fuzzily defined. These cases are labeled by domain experts as unusual incidents, in this paper we will refer to them as **atypical events**. Such events are represented in EWID system by outliers (outlying reports). The main reason for outliers generation is presented in Introduction. In this section we define and categorize the outliers.

For the sake of clarity we need to specify the concepts used in this paper. By an **emergency** we understand the event that poses an immediate risk to health, life, property or environment, requiring urgent intervention of Fire Service, which takes place before rescue unit arrival. By an **emergency scene** we understand location in which emergency occurs, together with all persons, objects or elements involved in that emergency, as it is understood in firefighting theory. We define **fire and rescue (F&R) methods** as the set of all activities undertaken by Fire Service at the emergency scene. We define **F&R action** as all the methods used by the firefighters together with a course of emergent circumstances which take place after fire unit arrival, possibly as a result of application of F&R methods. An **incident** is an event which consists of both emergency and F&R action. A **report** is an information unit stored in the EWID system which describes a singular incident. The **outlying report** is a surprising veridical report which appears to be inconsistent with the subclass it should belong to.

In Table 1 we propose the categorisation of the outliers consisting of forms, kinds and sources. Since reports are computer representations of real phenomena, therefore outlying reports can be generated due to three different reasons: rare report occurrence with respect to other reports stored in the system (connected with reports themselves), atypicality of reported real phenomena according to domain experts knowledge (connected with represented phenomena) and incor-

Table 1. The forms, kinds and sources of outliers.

Atypicality form	Atypicality kind	Atypicality source
1. Atypical emergency.	1.1. Very rare occurrence in dataset.	1.1.1. Incorrect report submission.
		1.1.2. Real outlier.
	1.2. Unusual combination or number of elements, threats or objects at the emergency scene.	1.2.1. Incorrect report submission.
		1.2.2. Real outlier.
	1.3. Other circumstances.	1.3.1. Incorrect report submission.
		1.3.2. Real outlier.
2. Atypical F&R method.	2.1. Method does not exist in the firefighting theory (amateurish or innovative methods).	2.1.1. Incorrect report submission.
		2.1.2. Real outlier.
3. Atypical relationship between emergencies and methods.	3.1. Standard emergency & atypical method used.	3.1.1. Incorrect report submission.
		3.1.2. Real outlier.
	3.2. Atypical emergency & standard method used.	3.2.1. Incorrect report submission.
		3.2.2. Real outlier.
	3.3. Atypical emergency & atypical method used.	3.3.1. Incorrect report submission.
		3.3.2. Real outlier.

rectness of report submissions (connected with a representation relation between reports and modeled phenomena).

In Table 1 we pointed that a report can be classified as atypical because of three categories: 1) as emergency itself since it is unusual combination or it contains unusual number of elements, threats or objects at the fire ground from the perspective of fire service domain knowledge or it occurs very rarely in dataset, 2) as containing amateurish or innovative F&R methods from the perspective of fire service domain knowledge, 3) as containing atypical relationship between emergencies (parts of incidents) and F&R methods with specified three kinds of this relationship. In the case of first two categories, in searching for atypicality some standard universal methods (statistical, data mining or machine learning methods) can be used together with F&R knowledge domain oriented methods. In the case of third category, searching for atypicality is more complex since atypicality here depends on relations. Emergencies or F&R methods are atypical with respect to other F&R methods or emergencies appearing in a given incident. Finding the atypical relationship between emergences and methods using threats becomes possible. According to the firefighting theory any threat can not be left without reaction. Therefore if in some incident the threat was identified and there is no information about taking the appropriate action, then such incident can be classified as atypical.

3 Dataset

Our dataset consists of 291 683 F&R reports. They contain information about the incidents which Fire Service respond, from the years 1992 to 2011. Our set of the reports concerns the incidents which happend in Warsaw City and its surroundings. In this dataset 136 856 reports represent fires, 123 139 local threats and 31 688 false alarms.

Each of the reports consists of an attribute section and a natural language part. The attribute section contains 506 attributes fitted to describe all type of incidents. However depending on category of the incident, the number of non-empty attributes varies from 120 to 180 for the report. Most of the attributes are boolean (True/False) type but there are also numerical values (i.e. fire area, amount of water used).

The natural language (NL) part is an extension to the attribute part. It was designed to store information, which can not be represented in a form of a set of attributes. Unfortunately there is no clear regulation what should be written in the NL part. Therefore, in this part the full spectrum of information, from the detailed information including the time coordinates to the very general and brief descriptions can be found. The simple statistic reveals that NL part contains approximately three sentences that describe the situation at the fire ground, actions undertaken and weather conditions.

In factual aspects the data stored in the EWID contain information about persons, objects involved in the incident and methods used to eliminate the arisen threats.

In our experiments we used subset of this dataset. For the labeling (assigning threats), we selected by domain experts only reports which represent the fire of residential buildings category. The set consists of 31 556 reports. From this set 302 reports were labeled by the experts. We used these reports in our experiments described in Section 5.

4 Method

The biggest issue in analysing the data was the large number of dimensions. It leads to higher computational complexity, scalability problems and results in computing difficulties (huge hardware resources are needed). The vast number of dimensions makes communication with domain experts harder or even impossible due to limited cognitive resources of experts minds (such as attention and working memory). Experts are able to elaborate in a given moment relatively small numbers of attributes. This also decreases usability of conceptual lattices as visual tools supporting communication with domain experts. The dimensionality reduction by a domain experts driven attribute selection does not reflect the real complexity of the incidents. Moreover, in this way we loose the possibility of finding the outliers (for example when the incident has a very rare attribute not considered by the domain experts).

To solve the problem of dimensional complexity in searching dataset for outliers, we decide to add some more abstract (generalization) layer intermediating between analysed data and experts domain knowledge. This layer objective is to reduce the number of dimensions and keeping the specificity of the modeled phenomena at the same time. To construct the generalization layer, we chose threats which can appear at the emergency scene and objects which can suffer from these threats. Further we will refer to this generalization layer as *threats layer*.

The main goal of Fire Services activity at the fire ground is elimination or neutralisation of arisen threats. The specific emergency generate the specific threats. Similar emergency should generate similar threats. If for the similar emergencies (for example from the same category) there exists one with significantly different number of threats or the combinations of threats, then such an emergency can be described as atypical and might be treated as an outlier. Either the emergency is very rare or its internal structure of attributes is unusual. Our approach to searching for atypicality of emergency is based on threats layer. As we pointed out in the Section 2, searching for atypical relationships is more complex however it becomes possible by using threats layer. Since no threat can be left without a proper reaction therefore, if in some incident where a threat was identified and there is no information about taking any appropriate action, then this report is considered as a disruption of the relationship between threats and methods.

This approach allows us to reduce significantly the number of dimensions without loosing the information about complexity of the real phenomena. However in our reports database there is no information about threats related to the specific emergency. Our next step was labeling the reports by domain experts with appropriate threats generated by reported emergency. To eliminate this issue, we used the tactic of German Fire Service [2, 6]. After arriving at a fire ground or an emergency scene German commanders have to evaluate and recognise the appearing threats. In order to do this systematically and not to miss any of the threats they have to fulfill the Threats Matrix (in German – Gefahrenmatrix) [6]. The Threats Matrix helps to identify the threats emerging at the scene and the threatened objects. This information plays a pivotal rôle in planning the further action. Having this information, commanders can recognize the primary danger that has to be eliminated at the outset and difficult point of action. The columns of the matrix represent threats, and the rows represent objects which can be threatened. The Table 4 depicts the Threats Matrix.

Table 2. The Threats Matrix used by German commanders. Legend: A1 – Fear, A2 – Toxic smoke, A3 – Radiation, A4 – Fire spreading, C – Chemical substances, E1 – Collapse, E2 – Electricity, E3 – Disease or injury, E4 – Explosion

Threat/object	A1	A2	A3	A4	C	E1	E2	E3	E4
People									
Animals									
Environment	–					–	–	–	
Property	–	–						–	
Rescuers									
Equipment	–	–						–	

In German language, column names are chosen so that they can be easily remembered. In order to help to memorize all threats by commanders, German threats' names were taken to form the following pattern: AAAA-C-EEEE *Angstreaktion, Atemgifte, Atomare Strahlung, Ausbreitung, Chemische Stoffe, Einsturz, Elektrizität, Erkrankung, Explosion.* The sign '–' in table indicates, that this threat in general can not threat this object. At the background of fulfilled Threats Matrix, German commanders define the Threat Focus and according to them organize their commanding. This tactic method is not used by the Polish Fire Services. In order to apply the Threats Matrix to EWID, we labeled the reports manually. The reports were analysed and labeled by students of the Main School of Fire Service Warsaw (abbreviation from Polish SGSP) that educates the officers of State Fire Service. Among the SGSP students there are also extramural students with commanding experience. From students who agreed to participate in our research, we selected three commanders having at least seven years experience in commanding. They were involved as *experts – practitioners* in labeling real action reports from EWID system.

We created the special system for reports labeling. Labeling process consists of two main phases: *tutorial phase* and *labeling phase*. Tutorial phase was focused on introducing the Threats Matrix and form of EWID incidents reports to experts. It was divided in to three consecutive parts. In the first part, experts were informed about Threats Matrix. In the second part a particular completed and discussed Threats Matrix was presented to experts. In the third part, experts received an exemplary EWID report together with Threats Matrix describing this report. Labeling phase consisted of many evaluating stages. In every evaluating stage experts were provided with one EWID report. On the ground of the information about incident described in the report, they were asked to evaluate threats which appeared during reported incident and to complete its Threats Matrix. Every expert was asked to label at least 100 EWID reports. Every report description was labeled by only one expert. In total we collected 302 labeled incident descriptions. From this dataset we created the FCA lattices and presented them to the SGSP's teachers, considered as *experts – theoreticians*. These teachers educate students in Tactic courses. They gave us their remarks how to rebuild the lattice or indicated interesting concepts.

The rest of the paper presents two examples of finding outliers supported by domain knowledge and using FCA methods.

5 Experiments

In this section we present the experimental results of the validation of our approach. At this stage of our research, the experiments conducted were mainly focused on evaluation of correctness of our model. Therefore, the obtained results should be interpreted as the preliminary results. We describe the experiments designed to evaluate the efficiency of reports' detection with two forms of atypicality: emergency and relationship. We conducted the experiments on described dataset with Concept Explorer[3] application version 1.3.

5.1 The Detection of Atypicality in Emergencies

As published in [7] there are three fundamental approaches to the problem of outlier detection: unsupervised (clustering), supervised (classification) and semi-supervised. In the current experiment we tried to detect the outlying reports according to the last category – a semi-supervised recognition [4, 11]. This approach needs pre-classified data but it only learns data marked as normal. It is suitable for static or dynamic data as it only learns one class which provides the model of normality. Systems which implement the approach, recognise an exemplar as normal if it lies within the (normality) boundary and as an outlier if it lies outside the boundary.

Taking into consideration the Fire Service's reports, the approach requires firstly the definition of the standard emergency – model of normality. The concept of the standard emergency is very difficult to define, mainly due to the variety of the emergencies (from fire to local threats). Despite narrowing the scope of emergencies to the lowest category (e.g. fire of residential buildings) we still have the problem with definition of the normality for this category.

We asked the domain experts (SGSP's instructors) to outline the standard scenario of residential buildings fires category. They were not able to solve this issue. They quoted many aspects of the construction of the buildings, thermal insulation existence, access to the building and equipment of firefighters which differentiate the emergencies. According to them, it was impossible to define the standard emergency (scenario) for such a category.

To eliminate the problem we constructed the formal context from the reports labeled with the threats by the commanders (extramural students). In this context the threats represented the attributes and the incidents – objects. Next, we created lattice from this context. Figure 1 depicts the lattice created.

[3] `http://conexp.sourceforge.net/`

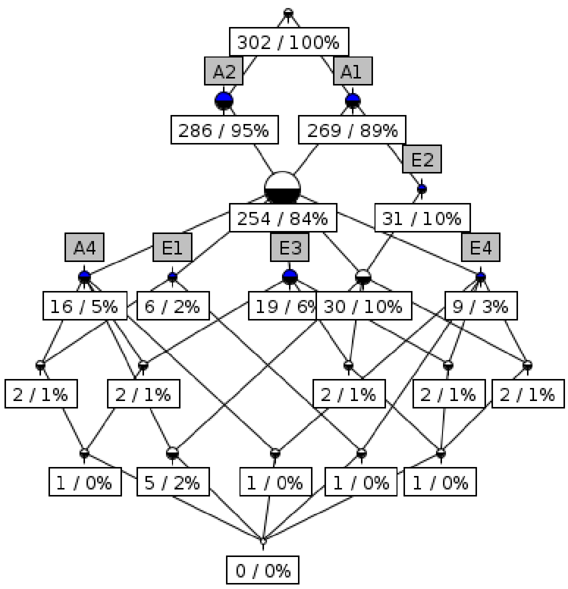

Fig. 1. The line diagrams of threats-incidents lattice.

The obtained lattice is very expressive. In the top-center of the lattice the large node is located. The node defines the concept of emergencies with two threats: A1 – Fear reaction and A2 – Toxic smoke. The node has a large number of own formal objects – 190 (63%). The own objects are not contained within any of its sub-concepts [18]. The features of the node made us believe that the concept related to the node, may define the standard (normal) emergency for the given category. To verify this, we asked the same domain experts (SGSP's instructors) whether these two threats occur mainly at the fire ground of residential buildings. They confirmed. Next, we asked them if the emergency with these two types of threats may be interpreted as the standard emergencies. They agreed to it with one exception. There is another type of threat which should be mentioned while the residential buildings are on fire: A4 – Fire spreading.

To face the problem of discrepancy between the concept lattice and the opinion of the domain experts, we examined the issue in more detail. Finally we realised that these differences are due to perceiving the threats by theoretical (SGSP's instructors) and practical (commanders – extramural students) experts – who labeled the incidents. The practitioners assign the A4 threat only when there is no sufficient team or equipments to extinguish a fire. The theorists state that the A4 threat always exists if there is a combustible material near the one involved in the fire.

This statement confirmed that we can treat the emergencies with A1, A2 threats as a standard. The large node in the lattice (Figure 1) defines this concept. According to the definition of semi-supervised outlier detection, all the incidents outside these concepts should be treated as outlying reports. However, in our opinion the notion of normality is not crisp but fuzzy. It means that the reports lying closer to the concept of standard emergency are less likely to be outlier that those more distant. To validate our model we analysed in details, with help of the domain experts, all the incidents located far away from the standard emergency concept node. Each of those incidents had assigned more than four threats.

There were 9 emergencies in the lattice which contained more than four threats. According to the experts, 4 out of the 9 incidents were correctly submitted and they weren't real outliers. Rest of them were labeled as potential outliers.

The first report from the set was outlier of category 1.2 (see Table 1). It contained information about a fire of residential building. The owner of this apartment stored the explosive materials inside the apartment. There was an explosion reported during the rescue action. The objects involved in the fire and the scenario allowed us to treat the case as the real outlier. The emergency was so rare and at the same time dangerous, that was chosen for further discussion during courses.

The second report should be also considered as the outlier. However, its atypicality does not satisfy the classification rules presented in Table 1. Its atypicality was caused by the shortcomings of our methodology. The student who labeled the report, assigned too many threats to the common basement fire. This also implies that the methodology is somehow self-controlled.

The next case was also correctly detected as an outlier. However, the atypicality stemmed from improper relationship between the emergency and the methods. There was a overvaluation in equipment. The small fire of residential building involved 6 fire appliances and 27 rescuers. The source of atypicality was difficult to settle. It should have been caused by the incorrect report submission or it was really the wrong F&R method. To clarify this issue, we should have contacted the officer in charge during this incident.

The last two cases were outliers in the category of an atypical emergency, caused by the incorrect report submission. They were wrongly assigned to the category of residential building fires. The first of these two reports was a fire of garden gazebo, the second a small carpenter's workshop located in the residential property. Both of them should be allocated to another category.

The presented experiment demonstrates that there is a potential in detection of outlying reports with utilizing FCA approach. However, in order to evaluate its effectiveness, we can only use the precision measure. In this experiment precision equaled 0.55. At the current level of our research the other measures can not be calculated. We have not yet calculated how many outlying reports contains the dataset.

5.2 The Detection of Atypicality in the Relationship

In the second experiment we concentrated on a recognition of the outlying reports caused by atypical relationship between emergencies and methods used to eliminate them.

In compliance with the firefighting theory, all the threats which occurred at the scene should not be left without proper action. If some of the threats exist and there is no information in the report regarding the action focusing on their elimination, we can suspect that the report is an outlier. In contrary, if there is no information about some threat and there is information in the report about the method used for its elimination, we may consider this report as an outlier. In this experiment the main focus was on first issue: threats without proper F&R methods. For each of incidents labeled by students we extracted information about the used F&R methods. We chose only methods which are associated with residential building fire. That means: extinguishing, evacuation (all types of objects from Threats Matrix) and smoke removal. Figure 2 depicts the concept lattice for this subset.

In the lattice there are three large nodes which we took for the further examination. There are respectively: C1 – node with 55 own objects, C2 – node with 40 own object and C3 – node with 17 own objects. They define the formal concepts, which we describe as:

- C1 – emergencies where A1, A2 threats exist and only smoke removal was performed (Figure 3 a)),
- C2 – emergencies where A1, A2 threats exist and extinguishing and smoke removal were performed,
- C3 – emergencies where A1, A2 threats exist and there weren't any rescue activities (Figure 3 b)).

The formal concept C2 represents a proper relationship between emergencies and F&R methods. There was a fire and the firefighters undertook adequate actions (extinguishing and smoke removal). The formal concepts C1 and C3 reveal some peculiar scenarios. There was a fire and only smoke was removed (C1); and there was a fire and there were no activities performed by Fire Service (C3). These both types were considered as outliers. However, the large number of own objects in these concepts (72) indicated that the problem was more systemic.

After deeper investigation it appeared that the problem was related to the definition of the attributes in EWID system. In the system there are three attributes (without natural language part) allocated to store information about extinguishing: *water stream used in the attack, water stream used in the defence* and *amount of extinguishing agent used*.

The reports that belonged to the C1 or C3 category were mostly small fires i.e. cooking meals left on an oven unattended. The firefighters extinguished this

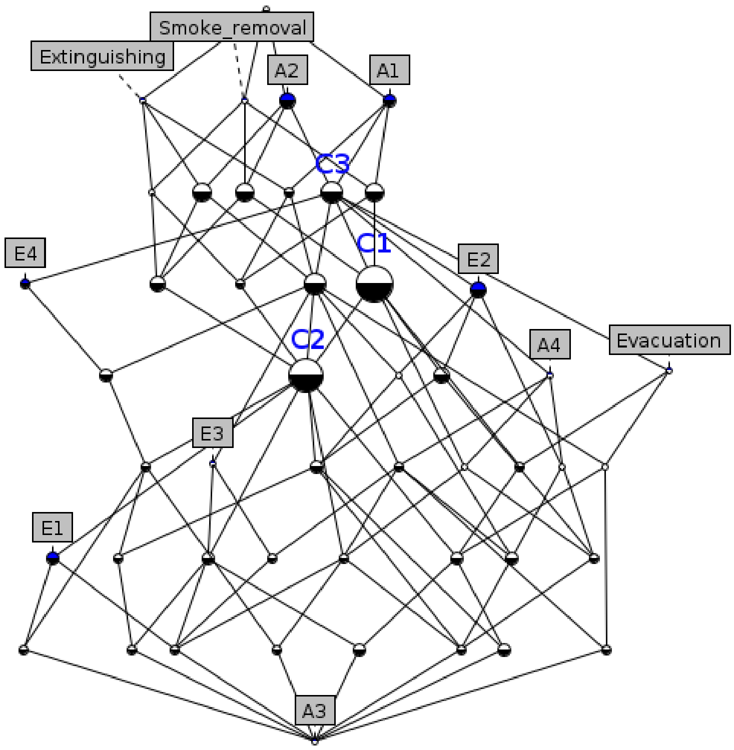

Fig. 2. The line diagrams of lattice of the threats, F&R methods and incidents.

type of fire using water from a tap or a bucket. According to the commanders opinions, who managed the firefighting actions and submitted the reports, these activities did not meet any of the outlined attributes. They used neither water stream nor water from fire appliances. Therefore, all the attributes were left empty. This selected concepts did not define the outlying reports according to our classification. However, the problem has negative impact on the statistical analysis that why it can be the starting point for the further improving of the EWID system.

To detect the atypical relationship between emergencies and F&R methods we performed some extended analysis. We tried to find the description of firefighting activities in NL section. The method is based on selecting by the experts the set of 17 words which may express the extinguishing activities. Firstly we lemmatized the NL part of the reports. The lemmatization allowed us to recognise the selected words, even if they were in the inflexed form. Then, we created the Document Term Matrix (DTM). The rows of this matrix represented the reports, the columns the set of words which appeared at least once in the NL part. In order to obtain one attribute that express extinguishing activities, we sliced the DTM, selecting only columns which contained words from the experts

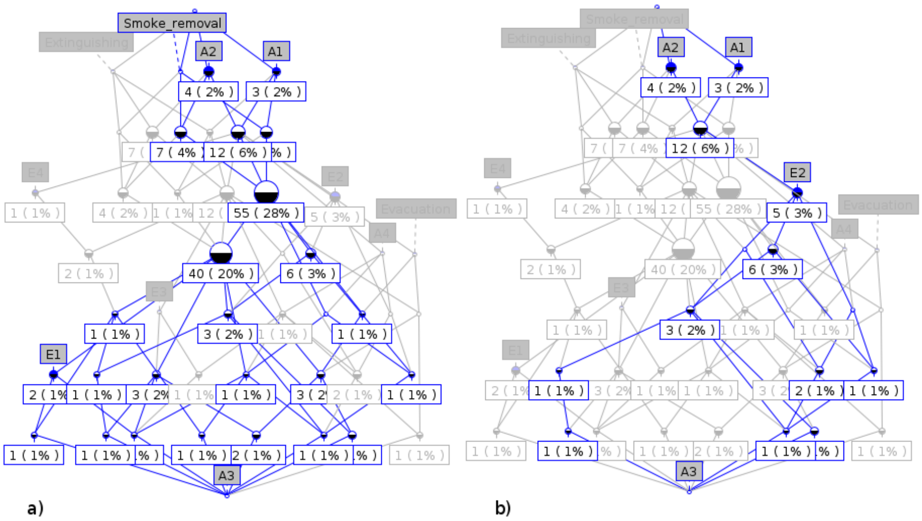

Fig. 3. The line diagrams of lattice of threats, F&R methods and incidents with selected concepts C1 and C3.

set. Then we run a logical OR on the previously selected columns. We obtained one column which represented the extinguishing activities mentioned in the NL part of the report. Finally, we perform a logical OR of this column with the columns from attribute section which represented the extinguishing. The final column showed the extinguishing actions marked either in the attribute part or NL part. We updated our formal context and created a new lattice. Figure 4 depicts the obtained results.

According to the lattice, there is one large node which represents a concept of most often appearing threats and proper F&R methods of their elimination. There are two nodes left (C4, C5) with 3 own objects where the threats exist and there are no rescue activities. After more detailed analysis done in the co-operation with experts, we came to the conclusions that they were false alarms. That means that they should be categorised as outlying reports caused by the incorrect report submission.

6 Conclusions and Further Work

The Incident Data Reporting Systems (in our case EWID) are the vast source of information. They contain description of threats which may appear at the scene and F&R methods to deal with them. In this dataset there are reports which describe very rare or atypical incidents as well as methods which are not in accordance with firefighting theory. Those reports should be detected and analysed to avoid serious accidents in the future.

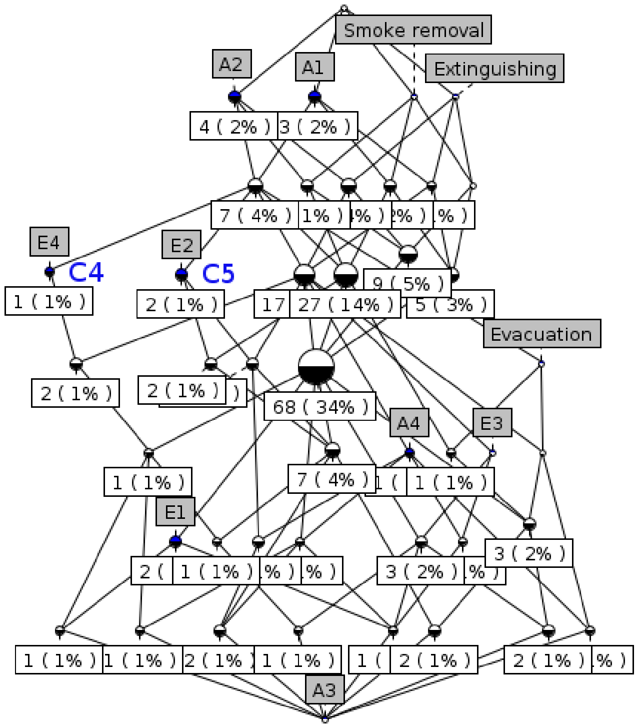

Fig. 4. The updated diagrams of lattice of threats, F&R methods and incidents.

The problem of detecting the outlying reports is very complicated. Due to a large number of attributes, description in natural language and atypicality in the internal structure of the reports, the problem cannot be cleared by statistical methods. The robust algorithms that can detect the outlying reports should include knowledge of domain experts. FCA can be of significant importance for Fire Service's analysts who are interested in the proactive detection of atypical or rare incidents. FCA is one of the few techniques that can be used by domain experts to interactively expose, investigate and refine the underlying concepts and relationships between them.

In this paper we described a methodology for improving the detection of outlying Fire Service's reports. The method is based on domain knowledge and dialogue with Fire & Rescue domain experts. The issue of large number of attributes was solved by introducing an abstract (generalization) layer intermediating between analysed data and experts domain knowledge. To construct the generalization layer, we chose threats which can appear at the incident scene and objects, that can suffer from these threats.

The preliminary experiments show that there is a potential in utilizing the FCA in detection of outlying reports. There were many types of outliers successfully detected. It would be more difficult to find them with utilizing statistical methods. Moreover, FCA assisted in finding the systemic error in submission of the reports to the EWID system. FCA also revealed differences in perceiving the threats by the practitioners and theoreticians.

One of the most important problems, which has not been addressed yet is the scalability of our approach. The fist stage of our method is based on the manual labeling of the incidents by the domain experts. This is not an issue for the German or USA Fire Services where firefighters assign threats to the incidents at the fire ground. However, in the case of the State Fire Service of Poland there is no such a procedure and we recommend assigning AAAA-C-EEEE terms to the rough reports. Before introducing this procedure, the problem is complex and requires multi-label classification and should be solved in the further work – hopefully we can succeed in this field, due to our experience in this domain, including involvement in projects [10] and data mining competitions [9]

Discovering the outliers in the whole dataset at once would be problematic. Analysing 7 million of incidents in one context would be impossible due to system resources and restrictions of FCA-presenting the analysis to the experts. However, the primary use of the solutions is to support the HQ analysts in their daily work. Every day ca. 1 500 reports must be checked against their validity and atypicality. These incidents can be easily divided into three groups: fires, local threats and false alarms. The number of incidents in are as follows: 50% fires, 42% local threats and 8% false alarms. False alarms won't be considered, so what must be comfortably fit on computer display is ca. 750 fires and even less local threat (these two will be treated separately).

The final system detecting outlying reports should not be limited to just one module, e.g. FCA. That means, the system should contain the set of classification, clustering and other algorithms combined in a form of ensemble. The ensemble methods use multiple models to obtain better predictive performance than could be obtained from any of the constituent models[4].

Acknowledgements: The authors would like to thank the students of NP-PS40 extramural study for their participation in this project and sharing of domain knowledge. Moreover, the authors would like to thank the Lecturers from the Section of Firefighting Operations of the SGSP, especially Lt. Col. Aleksander Adamski and Maj. Przemysław Wysoczyński.

The research has been supported by the research project realized within the Homing Plus programme, Edition 3/2011, of the Foundation for Polish Science, co-financed from the European Union Regional Development Fund, and by the grant 2011/01/D/ST6/06981 from the Polish National Science Centre.

References

1. Rozporządzenie Ministra Spraw Wewnętrznych i Administracji z dnia 29 grudnia 1999 r. w sprawie szczegółowych zasad organizacji Krajowego Systemu Ratowniczo-Gaśniczego. Dz.U.99.111.1311 §34 pkt. 5 i 6

[4] `http://en.wikipedia.org/wiki/Ensemble_learning`

2. Bundesamt für Bevölkerungsschutz und Katastrophenhilfe: Feuerwehr-Dienstvorschrift 100 Führung und Leitung im Einsatz : Führungssystem. FwDV 100 Stand: 10. März 1999
3. Elzinga, P., Poelmans, J., Viaene, S., Dedene, G., Morsing, S.: Terrorist threat assessment with formal concept analysis. In: 2010 IEEE International Conference on Intelligence and Security Informatics (ISI). pp. 77–82. IEEE (2010)
4. Fawcett, T., Provost, F.: Activity monitoring: Noticing interesting changes in behavior. In: Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining. pp. 53–62. ACM (1999)
5. Ganter, B., Wille, R.: Formal concept analysis. Springer Berlin (1999)
6. Graeger, A., Cimolino, U., de Vries, H., Sümersen, J.: Einsatz-und Abschnittsleitung: Das Einsatz-Führungs-System (EFS). Ecomed Sicherheit (2009)
7. Hodge, V., Austin, J.: A survey of outlier detection methodologies. Artificial Intelligence Review 22(2), 85–126 (2004)
8. Holmes, M., Wang, Y., Ziedins, I.: The application of data mining tools and statistical techniques to identify patterns and changes in fire events (2009)
9. Janusz, A., Nguyen, H., Ślęzak, D., Stawicki, S., Krasuski, A.: JRS'2012 Data Mining Competition: Topical Classification of Biomedical Research Papers. In: Proceedings of the Rough Sets and Current Trends in Computing (RSCTC 2012), Chengdu, China, August 17-20, 2012. Lecture Notes in Computer Science, vol. 7414, pp. 422–431. Springer (2012)
10. Janusz, A., Świeboda, W., Krasuski, A., Nguyen, H.S.: Interactive Document Indexing Method Based on Explicit Semantic Analysis. In: Proceedings of the Joint Rough Sets Symposium (JRS 2012), Chengdu, China, August 17-20, 2012. Lecture Notes in Computer Science, vol. 7415, pp. 156–165. Springer (2012)
11. Japkowicz, N., et al.: A novelty detection approach to classification. In: International Joint Conference on Artificial Intelligence. vol. 14, pp. 518–523. Lawrence Erlbaum Associates LTD (1995)
12. Krasuski, A., Kreński, K., Łazowy, S.: A Method for Estimating the Efficiency of Commanding in the State Fire Service of Poland. Fire Technology 48(4), 795–805 (2012)
13. Krasuski, A., Ślęzak, D., Kreński, K., Ł azowy, S.: Granular knowledge discovery framework. New Trends in Databases and Information Systems pp. 109–118 (2012)
14. Kreński, K., Krasuski, A., Łazowy, S.: Data mining and shallow text analysis for the data of state fire se rvice. In: Proceedings of Concurrency, Specification and Programming - XXth International Workshop, CS&P 2011. pp. 313–321 (2011)
15. Poelmans, J., Elzinga, P., Dedene, G., Viaene, S., Kuznetsov, S.: A concept discovery approach for fighting human trafficking and forced prostitution. Conceptual Structures for Discovering Knowledge pp. 201–214 (2011)
16. Poelmans, J., Elzinga, P., Viaene, S., Van Hulle, M., Dedene, G.: Gaining insight in domestic violence with emergent self organizing maps. Expert systems with applications 36(9), 11864–11874 (2009)
17. Poelmans, J., Elzinga, P., Neznanov, A., Viaene, S., Kuznetsov, S.O., Ignatov, D.I., Dedene, G.: Concept Relation Discovery and Innovation Enabling Technology (CORDIET). CoRR abs/1202.2895 (2012)
18. Willmor, D., Embury, S.M.: An intensional approach to the specification of test cases for database applications. In: Proceeding of the 28th international conference on Software engineering. pp. 102–111. ACM Press, New York (2006)
19. Xiangxin, L.: Rational judging method of fire station layout based on data mining. In: 2nd IEEE International Conference on Emergency Management and Management Sciences (ICEMMS), 2011. pp. 455–458. IEEE (2011)